

# AI Chess Assistant - Final Report

## Project Option: Incorporate ML Model in a New Use Case Setting

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### Abstract

Chess is one of the most played games worldwide. And, it is one of the games that requires practice and consistent learning to be good at it; having a good tutor is one of the best ways to learn chess. Not everyone will have the money afford private tutoring or time to attend a school to learn. There are several online sources that teaches you chess through lessons and puzzles. But such websites don't provide tutoring services, human or AI, so that the students will be able to discuss their strategies during the game. In this project we've developed a software with AI based chat bot integration that lets the users discuss their moves while playing the game. The software also includes Stockfish chess engine integration; it is one of the best chess engines as of date. Based on our experimental queries, we discovered chat bot was able to predict the next best move which was the same move predicted by the Stockfish engine. The chat bot was also able to discuss the game strategies with clarity. Therefore, we are confident that this project is production ready and can be used for real-life use.

## 1 Motivation and Objective

Chess is one of the games that players can become experts with dedicated practice[Campitelli and Gobet 2008]. There are online platforms such as *Chess.com*[Chess.com Developers 2025] that lets it's users play against each other online. Also, such sites offers lessons to help people learn chess. But doesn't offer live chat bot to discuss the moves while the player is learning.

This concurs with the 2020 study, [Dong and Miao 2020], which clearly states *"The results show that chess online educational products were rich in content and full featured, which could be divided into four categories: overall ecology, video tutorial, tactical training, live broadcast product. However, products still need to improve in product positioning and user experience to promote the development of chess online education."*

Based on the above papers and our own study, existing online chess tutoring services use the following methods to teach:

- **Puzzles:** Daily and weekly puzzles with different chess board configurations to simulate various scenarios.
- **Lessons:** On different chess openings, midgame and endgames strategies.
- **Play with computer:** Offers game with non-human players with option to select the difficulty level.
- **Discussion forums:** People are encouraged to discuss their games and strategies with other users.
- **Online private tutoring:** Chess tutors post their availability on sites such as Fiverr[Fiverr 2025].

Even with all this, we discovered the need to have live tutor that's flexible, time and money-wise, to help students learn chess.

Therefore, by this project we aim to develop an AI chess assistant that will help the users learn chess by helping them understand

game strategy and best possible move using a chess engine and an AI powered chat bot.

Our objective includes implementing Nibbler[git [n. d.]b] an open-source chess UI along with Stockfish[Stockfish Developers 2025] chess engine to get the best possible move. And add a chat bot alongside the chessboard, powered by Llama[Grattafiori et al. 2024] - Large Language Model(LLM), so that the user can discuss and learn move the best move and understand the game strategy better. In order to use the LLM within the chess context, we planned to fine-tune it with the [Mitchell J 2025] dataset so that the model will be very familiar with winning moves. And finally use Ollama[git [n. d.]a] an open-source project to host the model server.

## 2 Existing Work

In [Hassabis 2017], Demis Hassabis reflects on Garry Kasparov's famous 1997 defeat to IBM's Deep Blue and its lasting impact on the field of artificial intelligence. Reviewing Kasparov's book *Deep Thinking*, Hassabis highlighted how the match was a turning point, showing both the potential and limitations of machine intelligence. He emphasized that the real future of AI lied in collaboration - creating systems that can work with humans.

There were several studies exploring AI-driven chess teaching systems, AI driven approaches, and chess engine advancements. [Silver et al. 2017] introduced AlphaZero, which demonstrated superhuman performance in chess using reinforcement learning without human intervention. [Schrittwieser et al. 2020] worked on that work by mastering multiple games without prior knowledge of the rules. However, both AlphaZero and MuZero are designed for optimal play, not for teaching or explaining moves the best moves. Our approach combines Stockfish[Stockfish Developers 2025] with an AI-powered chat bot to explain moves in real-time as per user's demand.

[Campitelli and Gobet 2008] studied the role of practice in chess expertise, highlighting cognitive and psychological factors in learning the skill. However, their study does not explore AI-driven tools for tutoring. Similarly, [Gobet and Campitelli 2006] examined the influence of memory and practice in chess learning, but their work does not provide interactive AI-powered chat bot. Our project aims to address this by using a AI-powered chat bot.

[McIlroy-Young et al. 2020], a chess AI trained on human games, predicted moves that human players would most likely make. However, it lacked interactive explanations or the ability to engage with users. [Sadikov et al. 2006] developed an intelligent teaching system for teaching chess endgames, but their system was restricted only to specific scenarios. Our project overcomes these limitations by offering interactive move analysis in all phases of the game.

[Touvron et al. 2023] introduced LLaVA, a large multimodal language model that enables advanced visual-linguistic reasoning. [Liu et al. 2023] further improved this model for multimodal tasks, making it highly adaptable for chess-related applications. However,

LLaVA[Liu et al. 2023] has not yet been extensively applied to chess learning. Our system instead leverages Llama[Grattafiori et al. 2024], the model on which LLaVA[Liu et al. 2023] is based on, to recognize board states and generate explanations by getting the states directly from the code without any images.

Several studies have examined AI-assisted chess learning. [He et al. 2019] proposed a deep-learning-based framework for chess analysis, but it focused on move evaluation rather than tutoring. [Wang et al. 2019] reviewed the evolution of chess engines, emphasizing improvements in the algorithms without addressing their educational applications. [Müller et al. 2009] discussed chess engine tuning techniques, which are valuable for competitive play but not for interactive learning. Our project bridges this gap by making Stockfish[Stockfish Developers 2025] an interactive teaching tool rather than just a strong engine.

[Tee et al. 2021] examined chat bot-based chess tutoring, showing the potential for interactive AI learning tools. [Knight and Riddle 2018] studied how chess can enhance cognitive and strategic learning, but their work does not use AI for move analysis. [Li and Zhang 2018] introduced Chessbot, a robotic chess-playing system that combined computer vision and AI. However, its primary focus was on gameplay rather than explanation. Our approach uses Llama[Grattafiori et al. 2024] LLM model with a Stockfish[Stockfish Developers 2025] chess engine, ensuring both high-level gameplay and interactive tutoring.

Despite the progress in chess AI, a gap remains in providing real-time, interactive tutoring that combines the analytical strength of chess engines with natural language explanations. Our project seeks to address this by using Stockfish[Stockfish Developers 2025] with Llama[Grattafiori et al. 2024], allowing users to discuss their moves and game strategy.

### 3 Dataset

The project used [Mitchell J 2025] dataset to fine-tune the Llama[Grattafiori et al. 2024] model. The dataset contains 20,058 past games stored as a csv with 16 columns as mentioned below.

- **id**: A unique identifier for each game.
- **rated**: A boolean value indicating whether the game was rated (True) or casual (False).
- **created\_at**: The timestamp indicating when the game was created.
- **last\_move\_at**: The timestamp of the last recorded move in the game.
- **turns**: The total number of moves played in the game.
- **victory\_status**: The method by which the game ended (e.g., *mate*, *resign*, *timeout*).
- **winner**: Specifies whether the winner was *white* or *black*.
- **increment\_code**: The time control format used in the game (e.g., "5+10" means 5 minutes with a 10-second increment).
- **white\_id**: The username or identifier of the player controlling the white pieces.
- **white\_rating**: The Elo rating of the white player at the time of the game.
- **black\_id**: The username or identifier of the player controlling the black pieces.

- **black\_rating**: The Elo rating of the black player at the time of the game.
- **moves**: A sequence of moves played in the game in standard algebraic notation.
- **opening\_eco**: The Encyclopedia of Chess Openings (ECO) code associated with the opening played.
- **opening\_name**: The descriptive name of the chess opening used in the game.
- **opening\_ply**: The number of moves that define the opening phase of the game.

Fig. 1. Original dataset

#### 3.1 Original Dataset Statistics

The following are the statistics on the various variables in the original dataset.



Fig. 2. Rating statistics

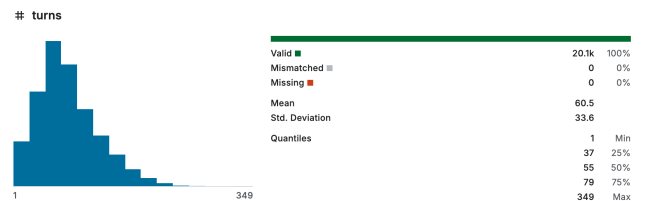


Fig. 3. Turns statistics



Fig. 4. Victory status statistics

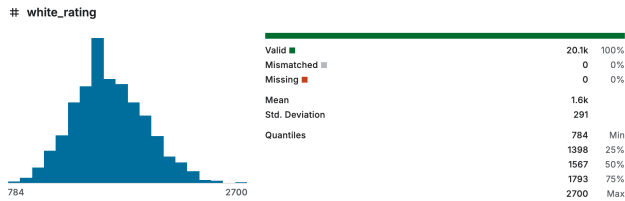


Fig. 5. White-rating statistics



Fig. 6. Winner statistics

### 3.2 Modified Dataset

The dataset contained columns irrelevant to the fine-tuning of our LLM. Columns such as *id*, *rated*, *created\_at* which are non-exhaustive, were irrelevant to the fine-tuning of our model. Therefore, we removed these columns and kept only the relevant ones. The descriptive name of the chess opening was added to the dataset. Here is the Python script to create a modified dataset.

#### Selecting Relevant Columns

- Only the columns essential for prompt and response generation are retained:
  - victory\_status, winner, white\_rating, black\_rating, moves, and opening\_name.
- This step extracts the data most useful for generating descriptive human-like narratives about the games.

#### Defining the Prompt-Response Generator

- A function named `format_humanized_prompt` was defined, which took a row of the dataset and returned a dictionary with two keys: `prompt` and `response`.
- The prompt was designed to resemble a user's natural-language query about the chess game. It included questions like:
  - "What is the name of the opening?"
  - "Who won?"
  - "How did the winner win?"
  - "Can you predict the ratings of the players?"
- The game's moves were appended to these questions for context.

#### Generating a Human-Like Response

- The function also constructed a response that sounds like a natural reply from an assistant:
  - The name of the opening was referenced.
  - The winner was mentioned.

- The method of victory was clarified — e.g., "outof-time" was replaced with "timeout".
- An estimate of the players' ratings were included to give the model a better understanding of the players.

#### Transforming the Dataset

- The `format_humanized_prompt` function was applied to each row of the DataFrame using `df.apply(..., axis=1)`.
- The result was a list of dictionaries each with a `prompt` and `response` suitable for instruction tuning.

#### Saving to JSONL Format

- The generated prompt-response pairs were saved to a file named `chess_humanized_prompts.jsonl`.
- Each dictionary is serialized to a JSON string and written line-by-line, which is the standard format for large-scale language model fine-tuning datasets.
- `ensure_ascii=False` was used to preserve any special characters.

We chose the following headers to build our new dataset as we felt that these were the most relevant ones to be learned:

- victory\_status:** The method by which the game ended (e.g., *mate*, *resign*, *timeout*).
- winner:** Specifies whether the winner was *white* or *black*.
- white\_rating:** The Elo rating of the white player at the time of the game.
- black\_rating:** The Elo rating of the black player at the time of the game.
- moves:** A sequence of moves played in the game in standard algebraic notation.
- opening\_name:** The descriptive name of the chess opening used in the game.

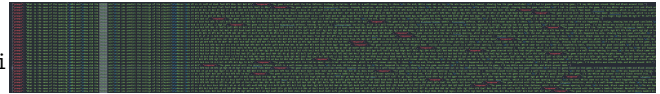


Fig. 7. Modified dataset

```

{
  "prompt": "What is the name of the opening?\nWho won?\nHow did the winner win?\nCan you predict the ratings of the players?\n\nMoves: \nd4 d5 c4 c6 cxd5 e6 dxe6 fxe6 Nf3 Bb4+ Nc3 Ba5 Bf4",
  "response": "The game started with the Slav Defense: Exchange Variation, which is a well-known opening in chess.\nIn the end, White came out on top.\nThe win happened by timeout, showing how the game concluded.\nIf I had to guess based on the game, I'd say White was around 1500 and Black around 1191."
}

```

Fig. 8. Single datapoint from new dataset

## 4 Our Approach

After a thorough analysis we designed our project to have three different components:

- Chess Engine
- Chess UI
- AI powered chat bot

We selected our individual components based on the following analysis.

### 4.1 Chess Engine

We explored several open-source chess engines, each with different strengths and functionalities. Leela Chess Zero (Lc0)[Developers 2023f] was a neural network-based engine inspired by AlphaZero, it utilized Monte Carlo Tree Search(MCTS) for move selection. It learned through self-play, making it highly adaptive but it required significant computational resources, particularly a GPU, for good performance. Berserk[Developers 2023b] balanced classical evaluation and neural network-based decision-making, offering fast and efficient response. Similarly, Ethereal[Grant 2023] focused on custom evaluation functions and traditional heuristics, making it efficient but less adaptable to modern AI-driven approaches.

For chess variants, Fairy-Stockfish[Developers 2023d] extended Stockfish’s capabilities to support non-standard formats like Crazyhouse and Fischer Random, making it a preferred choice for variant chess players. Schooner[Dugovic 2023] was a Rust-based multi-threaded engine designed for AI research and experimentation. Marvin[Developers 2023g] was another strong open-source engine, incorporating advanced pruning techniques to optimize search depth and improve efficiency. Texel[Trevithick 2023] emphasized positional play, using a tuned evaluation function to refine decision-making, making it a strong candidate for strategic chess analysis.

But among these engines, Stockfish[Stockfish Developers 2025] was the most powerful and widely adopted chess engine. It used advanced alpha-beta pruning, Efficiently Updatable Neural Networks, and a highly optimized search algorithm. Also, Stockfish[Stockfish Developers 2025] doesn’t use GPU acceleration and it had good Universal Chess Interface(UCI) support. Therefore, we chose Stockfish[Stockfish Developers 2025] as our chess engine for our AI chess assistant.

### 4.2 Chess UI

We explored several open-source chess UIs. Arena Chess GUI [Developers 2023a] was a widely used interface that supported UCI and WinBoard protocols. It provided features like engine tournaments and analysis tools, making it suitable for both casual and advanced users. However, its interface was outdated.

Scid vs. PC [vs PC Developers 2023] was another powerful GUI, known for its extensive database management features. It allowed users to maintain and analyze large collections of games and offered player statistics and opening preparation tools too. But its interface was outdated and required a learning curve for us. Cute Chess [Developers 2023c] had a clean and easy to use interface. However, it lacked advanced database features found in other UI frameworks.

Lucas Chess [Developers 2023e] was interface. It provides a variety of training modes and lessons, but it wasn’t feature-rich for advanced engine analysis in Stockfish[Stockfish Developers 2025].

Among these options, Nibbler [Developers 2023h] was the best choice for our project. It was a simple and easy to use framework. And, considering our experience we felt that this was easier to work with. It was a Node[nod [n. d.]] application so, knowing JavaScript was enough to modify the code per our requirements.

### 4.3 AI Powered Chat Bot

We compared a number of Large Language Models(LLMs) before deciding on Llama 3.1 to build an AI-driven chatbot that helps users to understand game strategy. We also considered the Claude 3, Mistral, and GPT-4 models.

GPT-4 [OpenAI 2023] from OpenAI was the most powerful proprietary LLM, due to its advanced reasoning capabilities and its extensive knowledge base. But it had its limitations since we could not fine-tune the model for chess-specific tasks due to its closed-source nature. Moreover, the incorporation of GPT-4 required interactions via API, which proved to be expensive.

Mistral [AI 2023b] was another alternative open-source, provides extraordinary efficiency and strong reasoning abilities. Although it offered a good balance of performance and computational cost, it did not have the extensive fine-tuning support or specialized instruction-following capabilities necessary for detailed chess strategy explanations.

Claude 3 [AI 2023a] by Anthropic was designed, focused mainly on conversational AI. Although it is effective at determining user requirements and offered thorough justifications, it was still a proprietary model, which made offline integration and customization impossible for our use case.

Llama 3.1 [Grattafiori et al. 2024] was the best option for our chess assistance chat bot after a thorough comparison. We may modify Llama for chess-specific insights because it is completely open-source, in contrast to proprietary models like GPT-4 and Claude 3. Llama had better instruction-following capabilities than Mistral and Falcon after comparing its performance through our interactions, which made it more useful for assisting players in analyzing intricate game strategies.

Thus, Llama 3.1 was the best option for our AI-powered chess assistant as it combined efficiency, advanced reasoning capabilities, and customizability.

The project used [Mitchell J 2025] dataset to fine-tune the Llama[Grattafiori et al. 2024] model.

At this point, we’ve set up Stockfish[Stockfish Developers 2025] along with Nibbler[Developers 2023h] in our local machine. The next step is to create a chat bot section on Nibbler[Developers 2023h] UI and connect the Llama[Grattafiori et al. 2024] model, fine-tuned with [Mitchell J 2025] dataset.

Users running Nibbler[Developers 2023h] will connect with the Ollama[git [n. d.]]a server to send and receive messages with the Llama[Grattafiori et al. 2024] model while playing the game.

#### 4.4 Fine-tuning

Before using the Llama[Grattafiori et al. 2024] model we had to fine-tune the model so that it will be able to answer chess related queries. The dataset we chose was not designed to be used to fine-tune LLMs. Therefore, we created a modified dataset using a Python script as mentioned before. So, the model has a better understanding of the past chess games to answer the queries. We also discovered that the model without fine-tuning gave a satisfactory performance, yet we went ahead with the fine-tuning process.

We followed the following steps to fine-tune the model:

- **Model and Tokenizer Initialization**

- Loaded the LLaMA 3.1 8B-Instruct model and tokenizer using the Hugging Face Transformers library.
- Enabled fast tokenization with `use_fast=True` for improved performance.
- Loaded the model in 4-bit precision (`load_in_4bit=True`) and used automatic device mapping (`device_map="auto"`) to distribute the model across all available GPU devices.
- This approach significantly reduces the VRAM required.

- **Dataset Loading and Preprocessing**

- Loaded a JSON Lines dataset file (`chess_humanized_prompts.jsonl`) that contains chess-related prompt-response pairs.
- Split the dataset into training and test sets with a 90/10 ratio using `train_test_split()`.
- Set the tokenizer's padding token to be the same as its end-of-sequence token to avoid errors during padding.
- Defined a custom `format()` function that wraps each prompt-response pair in special tokens used by the LLaMA instruction format:
  - \* Each example was structured with special markers like `<|begin_of_text|>`, `<|start_header_id|>user`, `<|end_header_id|>`, and `<|eot_id|>` to tell the model how to treat the text.
- The formatted text was then tokenized using the tokenizer, with a maximum sequence length of 2048 and padding to that maximum length.

- **Parameter-Efficient Fine-Tuning (PEFT) with LoRA**

- Used LoRA (Low-Rank Adaptation) to fine-tune only a small subset of parameters, greatly reducing memory requirements and training time.
- Configured the `LoraConfig` with:
  - \* Rank  $r = 8$ , `lora_alpha = 16`, and `lora_dropout = 0.05`
  - \* Targeted attention projection layers: `q_proj`, `k_proj`, `v_proj`, `o_proj`
- The model was then wrapped with `get_peft_model()` to apply the LoRA modifications.
- Printed the number of trainable parameters to verify that only a small fraction of the model is being updated during training.

- **Training Configuration and Execution**

- Created a set of training arguments specifying:

- \* Batch size of 1, gradient accumulation over 4 steps to simulate a batch size of 4.
- \* 1 epoch of training, with a learning rate of  $2 \times 10^{-4}$ .
- \* Mixed precision training with `fp16=True` for improved speed and lower memory usage.
- \* Logging every 25 steps and saving the model at the end of each epoch.
- Initialized a Trainer object, passing in:
  - \* The PEFT model and tokenizer
  - \* The training and evaluation datasets
  - \* A data collator for language modeling with `mlm=False`, meaning causal (not masked) language modeling is used.
- Started training using the `train()` method of the trainer.

- **Saving the Fine-Tuned Model**

- Saved both the model and tokenizer to the local directory `llama3-chess-finetuned`.
- This step ensures that the trained weights and tokenizer can be reused later or loaded for inference.

- **Merging LoRA Adapters and Uploading to Hugging Face**

- Reloaded the base LLaMA 3 model and loaded the fine-tuned adapter weights using `PeftModel.from_pretrained()`.
- Called `merge_and_unload()` to combine the LoRA adapter with the base model into a single unified model.
- Pushed the merged model and tokenizer to the Hugging Face Hub using `push_to_hub()` for public or private sharing.

#### 5 Results

As mentioned in the above section, we've set up Nibbler[Developers 2023h] along with Stockfish[Stockfish Developers 2025] engine. The following are the screenshots of the set up where two human players play each other in our environment. In the figure 9, you

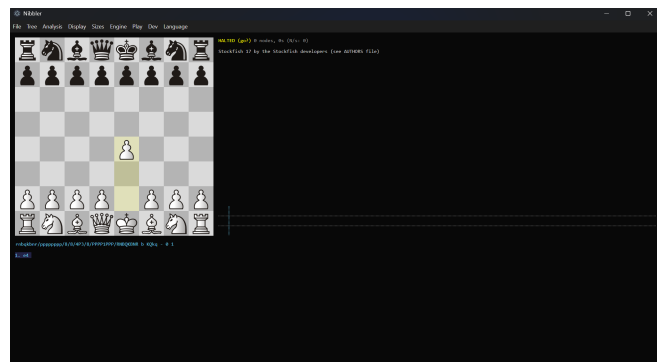


Fig. 9. Without Stockfish

could see that there aren't any analytics on the right hand side of the chessboard or on the board itself. But after integrating Stockfish engine, you could see in figure 10 that an arrow appears on the



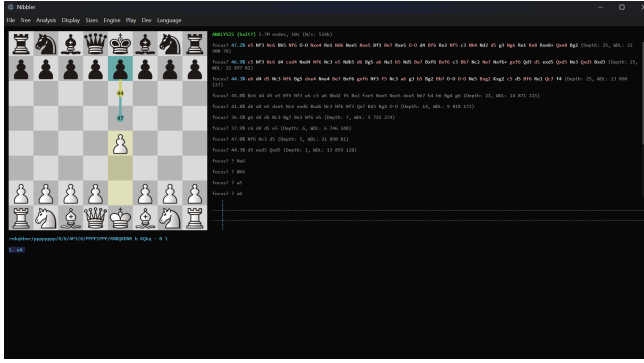


Fig. 10. First Move With Stockfish

board along with the score computed by the Stockfish engine along with the computation of the score on the right hand side of the board. As you can see in figure 11, the multiple moves are suggested

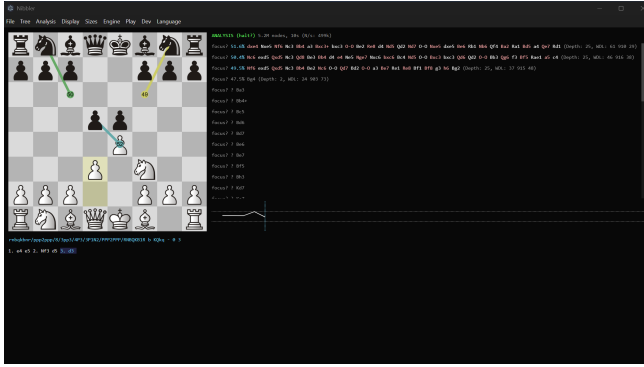


Fig. 11. Game Progression

with their Stockfish score. The user could choose the move with the highest score. After integrating the chat bot to the right-hand side we performed a few queries. Our goal was to test the model performance on the following tasks:

- (1) **Greetings:** Determine how the model will handle greetings by the player. Refer to figure 12.
- (2) **Understanding of opening moves:** We tested this by querying the model the name of the opening that we made as a white player. Refer to figure 13.
- (3) **Game strategy(determining next best move):** We wanted to test how the model will predict the next best move and provide an explanation. Therefore, we queried the best move as a white player. Refer to figure 14.
- (4) **Ability to understand opponent's move:** We asked the model what move might the opponent make based on our latest move. Refer to 15.
- (5) **Handling non-chess queries:** We asked the model a non-chess related question to determine how well the model was able to handle off-topic queries. Which was important to keep the focus on the game. Refer to figure 16.

The model performed exceptionally well on all our test queries and proved to be a good model to handling various possible scenarios.

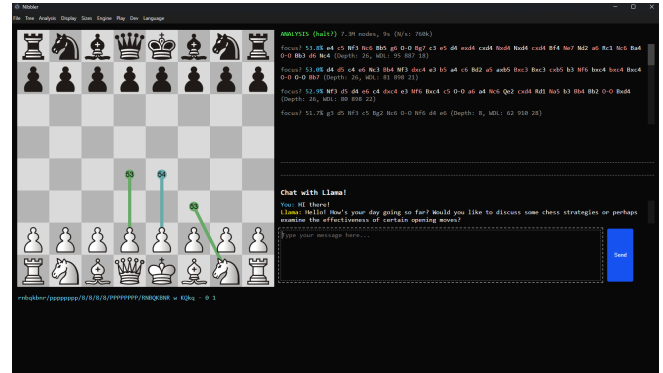


Fig. 12. Greetings

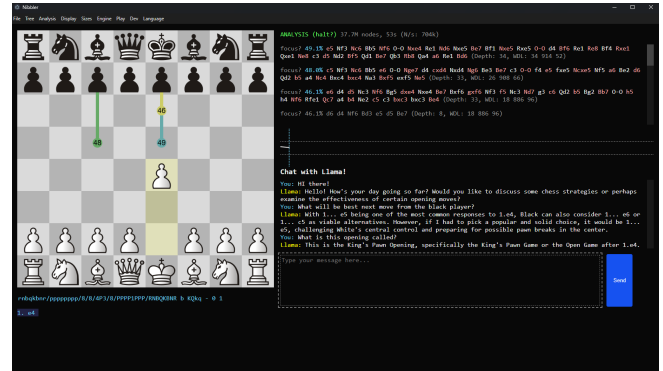


Fig. 13. Llama explaining opening move

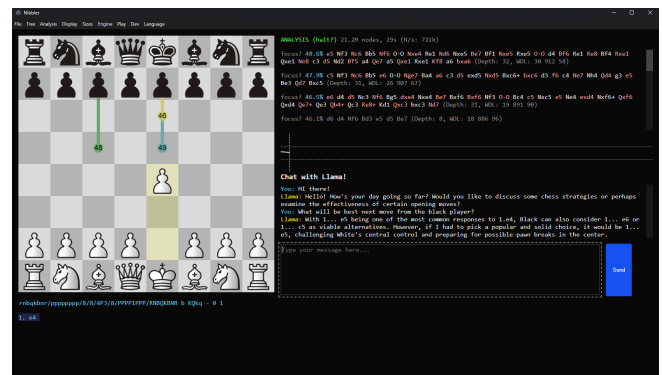


Fig. 14. Game strategy

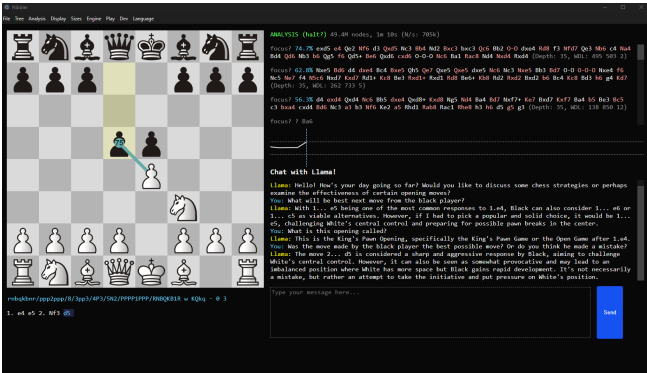


Fig. 15. Game discussion

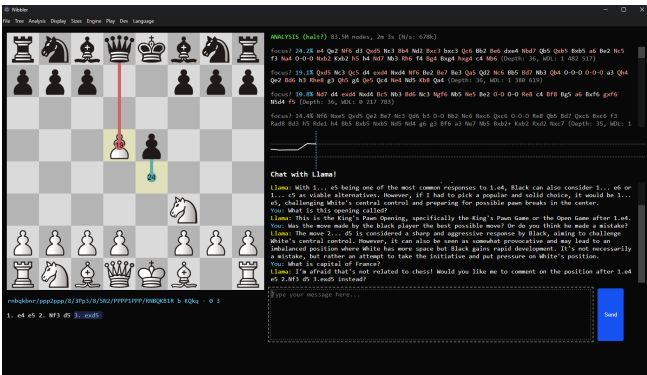


Fig. 16. Llama’s response to non-chess question

6 Conclusion

We successfully created a software integrated with an AI chat bot capable of helping its users to discuss and better understand game strategies during the game play. The LLM, Llama 3.1 model [Grattafiori et al. 2024] that we’ve used in our project was able to respond to chess-related queries and was in concurrence with the Stockfish[Stockfish Developers 2025] best move predictions. We believe that this software will be able to help people who are new to chess learn at a faster pace than the conventional approach of book-based or chess lessons offered by online services such as Chess.com [Chess.com Developers 2025]. We also feel that this will be beneficial for people who won’t be able to afford in-person chess lessons or people who have time constraints to attend such classes. At this point, the software requires Ollama[git [n. d.]a] server to be running locally and needs to be set up as a prerequisite for executing the main software. In future, this step could be avoided by hosting the model in a cloud-based server so, that the users need to only set up the main software.

7 Contribution Table

All the members equally contributed to this report. The following table 1 summarizes what each of the members contributed in addition to this report.

Member	Contribution
Vivek Viswam R. V.	System design, Nibbler, Stockfish, Fine-tuning and Ollama set up
Sheethal Urs	Llama and few other model comparison, Nibbler UI update assistance and assisted in fine-tuning step
Sai Mokshith Goud Palle	Studied Chess rating system and past works, tested queries

Table 1. Member Contributions

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